

Middlesex University Research Repository

An open access repository of

Middlesex University research

<http://eprints.mdx.ac.uk>

Turner, Anthony N. ORCID logoORCID: <https://orcid.org/0000-0002-5121-432X>, Jones, Ben, Stewart, Perry F., Bishop, Chris ORCID logoORCID: <https://orcid.org/0000-0002-1505-1287>, Parmar, Nimai ORCID logoORCID: <https://orcid.org/0000-0001-5540-123X>, Chavda, Shyam ORCID logoORCID: <https://orcid.org/0000-0001-7745-122X> and Read, Paul (2019) Total score of athleticism: holistic athlete profiling to enhance decision-making. *Strength & Conditioning Journal*, 41 (6) . pp. 91-101. ISSN 1524-1602 [Article] (doi:10.1519/SSC.0000000000000506)

Final accepted version (with author's formatting)

This version is available at: <https://eprints.mdx.ac.uk/27909/>

Copyright:

Middlesex University Research Repository makes the University's research available electronically.

Copyright and moral rights to this work are retained by the author and/or other copyright owners unless otherwise stated. The work is supplied on the understanding that any use for commercial gain is strictly forbidden. A copy may be downloaded for personal, non-commercial, research or study without prior permission and without charge.

Works, including theses and research projects, may not be reproduced in any format or medium, or extensive quotations taken from them, or their content changed in any way, without first obtaining permission in writing from the copyright holder(s). They may not be sold or exploited commercially in any format or medium without the prior written permission of the copyright holder(s).

Full bibliographic details must be given when referring to, or quoting from full items including the author's name, the title of the work, publication details where relevant (place, publisher, date), pagination, and for theses or dissertations the awarding institution, the degree type awarded, and the date of the award.

If you believe that any material held in the repository infringes copyright law, please contact the Repository Team at Middlesex University via the following email address:

eprints@mdx.ac.uk

The item will be removed from the repository while any claim is being investigated.

See also repository copyright: re-use policy: <http://eprints.mdx.ac.uk/policies.html#copy>

The Total Score of Athleticism:

Holistic Athlete Profiling to Enhance Decision Making

Abstract

Oftentimes, the coaching staff that make up the multidisciplinary team of a sports club or governing body require a single, holistic indication of an athlete's athleticism. Currently there is no consensus on how this is best achieved and thus the Total Score of Athleticism (TSA) may provide one such strategy. The TSA is derived from the average of z -scores (or t -scores in the case of small samples) from a sport specific fitness testing battery, ensuring athletes are judged across all the relevant fitness capacities that best define the physical demands of competition. To aid readers in using the TSA, this article also details how it is computed in excel.

Introduction

As strength and conditioning coaches, we regularly put our athletes through a range of fitness tests to monitor progress and make adjustments to their programs. Often, our results are also used to form a holistic judgement of an athlete by the sports club or governing body. In these instances, the psychologist, physiotherapist, and the technical coaches also grade the athlete, with the results determining future interventions and team selection. Such situations lend themselves to providing a single score for the athlete's physical fitness, rather than separately discussing scores for jumps, speed, or strength in a multidisciplinary team meeting for example. This approach is designed to streamline collaborative communication, maximizing the time available for planning and practical delivery.

Furthermore, coaches may not be as interested in the raw score of each athlete, as much as where the score ranked within their team, especially when there is competition for places. For example, a coach may have no concept as to what is deemed a good jump or back squat, with this information only becoming apparent through some analysis that reveals the score is amongst the highest or lowest in the squad. Also, it can be rare to have the athlete who achieved the highest bench press score also record the highest agility or Yo-Yo score for example, suggesting that there is some compromise amongst

the different components of athleticism that make up a good sports performer. So, while we want to rank how each athlete compared to their team mates across each test (to highlight test-specific strengths and weaknesses), we also want to be able to judge how they did holistically, i.e., have some measure of general athleticism, where moderate scores across all tests may in fact be more beneficial to performance, than scoring really high in some, while doing terrible in others. The aim of this paper is to describe a strategy which provides a single score of holistic fitness, referred to as the Total Score of Athleticism (TSA).

Using *standardized scores* and defining windows of opportunity

The Total Score of Athleticism (TSA) is derived by averaging a set of standardized scores (here, either z -scores for large groups or t -scores for small groups) from a series of tests undertaken by an athlete (Turner, 2014). A standardized score (of a single test), and therefore the TSA (of a series of tests), allows coaches to examine contextualised data of individual athletes relative to their teammates, and thus set benchmarks and training goals that are realistic to the demands placed on players by the club. For example, each player's physical capacity will to some extent, be a consequence of the coach's training philosophy, which determines competition tactics (or style of play) and their attitude towards strength and conditioning practices. Furthermore, results may also be a consequence of general time allocated to training (e.g., semi-professional athletes vs. professional athletes) and naturally, the age and maturation of the players (Till, et al., 2016). So, while comparative data may be available outside of the club, enabling comparisons with professional athletes for example, it may create unrealistic targets. This is because using comparative data may establish benchmarks or test goals, that require a time allowance to fitness training that is at odds with that allotted, and requires financial and logistical input that is not supported. Equally, comparative data drawn from other teams may represent a trend toward a particular set of fitness characteristics that maps back to a style of play that is not universally adopted. Finally, given it is likely that within-club comparisons will be used for team selection purposes, between-player comparisons are likely the most beneficial use of fitness testing data.

The usefulness of z -scores (the standardized score we will initially discuss) can be noted when we consider the following question. During a fitness testing battery, if an athlete squats 140 kg and has a beep (aerobic shuttle) test score corresponding to level 15, how

well did they do, and on which did they do best? The first stage of answering this is to establish the maximum values attained from each athlete, within the tested squad. For squats, the highest recorded score may have been 220 kg and for the beep test, level 17. Therefore, the athlete attained a score of 64% and 88% respectively, relative to the maximum. So, on a percentage basis, the athlete performed better on the beep test. However, the 88% on the beep test may have been one of the lowest scores amongst all test takers. Conversely, the 64% may have been one of the highest, so arguably, the athlete did best on the squats. Such information enables strength and conditioning coaches to more precisely highlight athlete strengths and weaknesses, and program accordingly. Therefore, the final piece of information used is a measure of how well someone did relative to all who took those tests. A z -score contains all of this information, and because it is unit-less, it enables comparisons between other tests which otherwise would not be possible (Jones, Till, Manley, & McGuigan, 2017; Turner, Total Score of Athleticism: a strategy for assessing an athlete's athleticism, 2014).

By plotting athlete data as z -scores, coaches, athletes, and sport scientists can get a quick and easy to read data point and graph, indicating how well each athlete did on each test relative to their team mates, and which areas are strengths, and which are weaknesses. For example, looking at Figure 1, where zero represents the team average, anything above the zero-line means that the athlete is better than average, and anything below, they are worse. Practically, this means that anything below the line represents a clear window of opportunity that should be targeted when individualizing the athletes next training program.

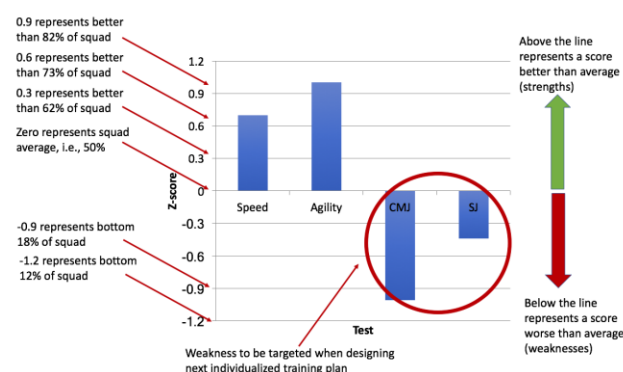


Figure 1. The z -score profile of an athlete represented here as a histogram.

The next question involves the interpretation of how good or bad they are at each test (relative to their teammates). For this we must be able to interpret the z -score value (on the y-axis), which corresponds to the height of each bar. To fully understand these values, the mean and standard deviation (SD) needs to be examined, whereby the former provides the average score and the latter the dispersion of data (a smaller standard deviation means that the dataset contains values that are, on average, close to the mean, while a larger SD suggests the opposite). Together, the mean ± 1 SD will contain $\sim 68\%$ of all test scores, the mean ± 2 SD $\sim 95\%$, and the mean ± 3 SD $\sim 99\%$ (see Figure 2 and Table 1). Z-scores rescale values to show how many standard deviations away from the mean they are and therefore have a mean of zero and a SD of one (Salkind, 2011). We can interpret values by using a normal distribution (refer to Figure 2). So, if an athlete scores $+2$, it indicates that the athlete scored 2 SD above the mean, meaning that they performed better than 97% of all scores (50% up to the mean plus 34% up to $+1$ SD and another 13% up to $+2$ SD). A score of $+1$ inform's us that they scored better than 84% of others who were tested, while -1 suggests 84% did better than them. So, when we analyze Figure 1 again, we must make note of the values on the y-axis to determine their test scores. For this reason, when producing charts for each athlete, it can be useful to fix the y-axis values (that is, use Excel's chart formatting function to manually set max and min values) to make interpretation easier and more accessible to coaches and athletes, by allowing them to simply gauge performance via the height of each bar (if y-axis values are not fixed, the histogram is plotted based on the largest y values).

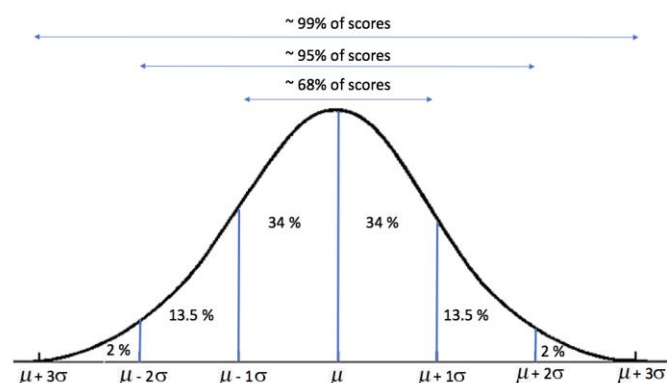


Figure 2. The mean \pm the SD. The mean \pm 1 SD contains ~ 68% of all scores, \pm 2 SD ~ 95% and \pm 3 SD ~99%. μ = mean and σ = SD

Table 1. Z-scores and the percentage of test scores they contain. This can be directly computed in Excel by using the “NORMDIST” function.

0		50%	
- 0.3	38%	0.3	62%
- 0.6	27%	0.6	73%
- 0.9	18%	0.9	82%
- 1.2	12%	1.2	88%
- 1.5	7%	1.5	93%
- 1.8	4%	1.8	96%
- 2.1	2%	2.1	98%
- 2.4	1%	2.4	99%
- 3.0	0%	3.0	100%

Finally, in sport, smaller values can of course be a sign of better performances, for example 30m-sprint time. Here negative values for z -scores would be produced for athletes who were better than average. When this occurs, the final value can simply be multiplied by -1. This reversing of positive values to negative values and vice versa, enables all scores above the line to be seen as an athlete’s strength and all scores below the line to be seen as an athlete’s weakness (relative to those who took the test); again, this adjustment simply makes for easier interpretation.

Calculating the Total Score of Athleticism

Coaches are often interested in one score that represents how “fit” a given athlete is. For this we can use the TSA, calculated by averaging the z -scores from each test (Turner, 2014). Using the average mitigates scenarios whereby an athlete is missing a particular test due to an injury for example. Leaving the cells blank ensures this is picked up when interpreting the graphs (see Figure 3). Another reason to average scores is to ensure the athlete is “well rounded”. For example, while an athlete may have a

very high score for the bench press, their score for some test of aerobic capacity could be low and in this case, the low score will neutralize the high score. The TSA is therefore indicative of the fact that sport often requires several athletic abilities; thus, athletes cannot just focus on one facet of physical performance at the expense of others. Similarly, researchers are also starting to use an averaging of z-scores to better understand in-competition metrics, by correlating this one measure of holistic fitness with key performance indicators such as tackles, shots and passes (Bunn, Ryan, Button, & Zhang, 2017; Long, et al., 2014; Wing, Turner, & Bishop, 2018). Again, this seems logical as on-field metrics are simultaneously driven by several physical competencies, working in concert with one another, and thus this represents a potentially fruitful addition to the traditional relationships identified between key performance indicators and single components of fitness (such as 30 m speed or 1 RM back squat).

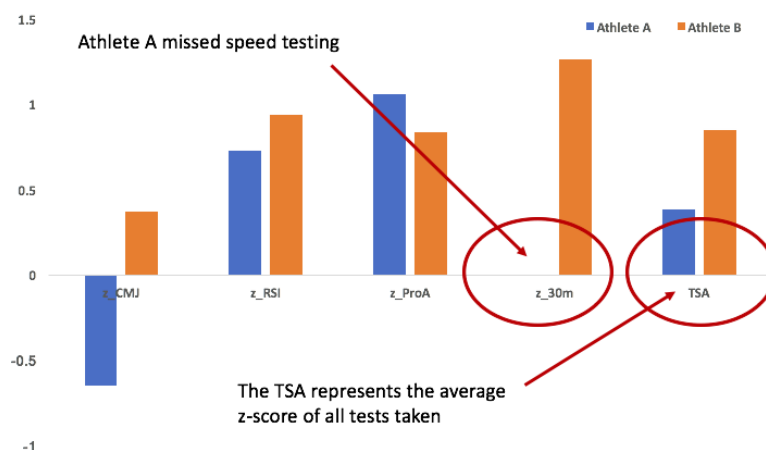


Figure 3. Using the z-score test profile to compare two athletes along with the total score of athleticism (TSA), which indicates who is the most “rounded” athlete relative to the chosen test battery.

Lastly, following the completion of a comprehensive needs analysis, a quick reference assessment of who is the most athletic (relative to the demands of the sport) can be plotted by graphing all athlete TSA scores (Figure 4). Interpretation can then be made easier still by sorting them in Excel (highest to lowest) or ranking athletes as described elsewhere (Turner, 2017) and below.

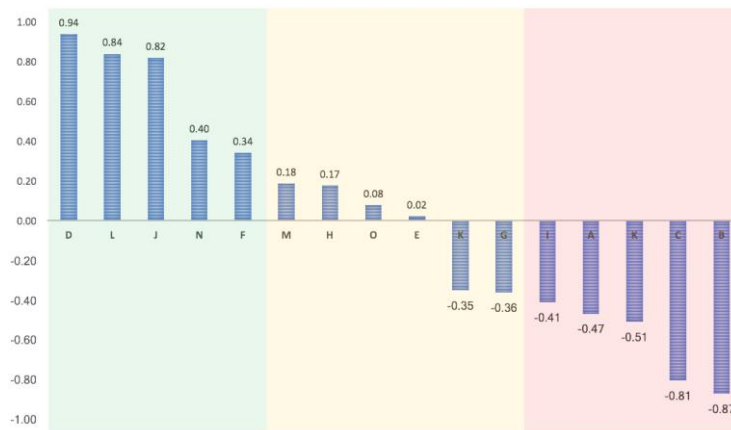


Figure 4. Plotting each athlete’s TSA score to determine who is most athletically prepared for the demands of competition. To ease interpretation, the TSA has been ranked from highest to lowest. Clearly all players should strive to be above the average line, however, in this example the top third (green), middle third (amber), and bottom third (red) have also been identified to conform with the common traffic light-based system often used.

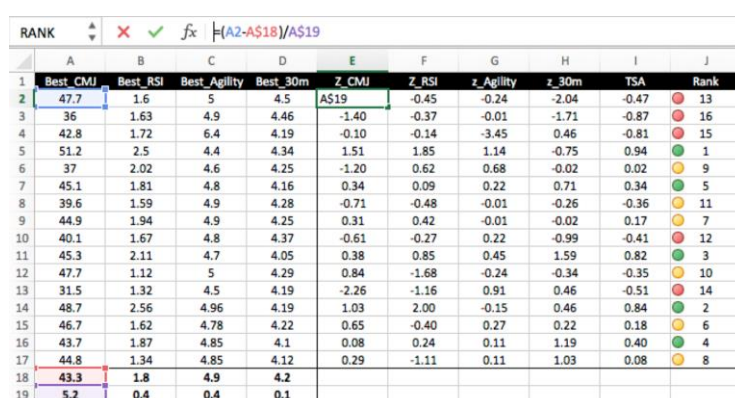
Determining the fitness testing battery

Given z -scores from each test are averaged, it is important to choose tests that represent the athletic components required of the sport in question. For example, choosing one test for strength, one for power, speed, aerobic capacity and so forth, ensures a rounded approach to athleticism. Having more tests geared towards strength and power assessment relative to aerobic capacity for example, is indicative of a requirement in athleticism centering on those qualities, perhaps because the sport event is highly intensive and of short duration, or that this particular combination better suits the specific positional demands. Whatever tests and weighting of tests are decided on, the validity of the TSA is governed by the tests used to make up its score. Using several tests that favor one attribute of athleticism (or giving one test a higher weighting), such as strength, will bias scores in its favor (Till, Scantlebury, & Jones, 2017). Practitioners therefore, should also consider splitting squad assessments by positional groups (judging soccer goalkeepers by aerobic capacity may disadvantage them for example).

Calculating the TSA and plotting graphs in excel.

To calculate the z -score of any given test, the squads average test score is subtracted from the athlete’s test score, then this value is divided by the squad’s SD; so the equation reads as follows: **$z\text{-score} = (\text{Athlete score} - \text{team mean}) / \text{team standard}$**

deviation. This can easily be computed in excel by using the “STANDARDIZE” formula, or inputted manually using the equation provided (and as illustrated in Figure 5). The formula contained within the cell (cell E2 in the example given in Figure 5) can then be dragged down and then across to compute *z*-scores for all athletes across all tests. However, before doing so, the test mean and SD must first be fixed using the “\$” sign as per the formula highlighted in Figure 5. Furthermore, for purposes of drawing graphs and to ensure scores above the line are seen as strengths, and those below the line are seen as weaknesses (as per Figure 1), multiply speed-based time-tests by -1 (see Figure 6). Finally, the TSA is calculated by averaging all *z*-scores (Figure 7). For ease of interpretation for coaches and athletes, the TSA and each test’s *z*-score, can then be ranked and a “traffic light” system can be used (Figure 8) to highlight how each athlete’s fitness compares to their team mates; an example of how this can be presented (using the “VLOOKUP” function) is shown in Figure 9.



	A	B	C	D	E	F	G	H	I	J
1	Best_CMJ	Best_RSI	Best_Agility	Best_30m	Z_CMJ	Z_RSI	z_Agility	z_30m	TSA	Rank
2	47.7	1.6	5	4.5	$(A2-\$A\$18)/\$A\19	-0.45	-0.24	-2.04	-0.47	13
3	36	1.63	4.9	4.46	-1.40	-0.37	-0.01	-1.71	-0.87	16
4	42.8	1.72	6.4	4.19	-0.10	-0.14	-3.45	0.46	-0.81	15
5	51.2	2.5	4.4	4.34	1.51	1.85	1.14	-0.75	0.94	1
6	37	2.02	4.6	4.25	-1.20	0.62	0.68	-0.02	0.02	9
7	45.1	1.81	4.8	4.16	0.34	0.09	0.22	0.71	0.34	5
8	39.6	1.59	4.9	4.28	-0.71	-0.48	-0.01	-0.26	-0.36	11
9	44.9	1.94	4.9	4.25	0.31	0.42	-0.01	-0.02	0.17	7
10	40.1	1.67	4.8	4.37	-0.61	-0.27	0.22	-0.99	-0.41	12
11	45.3	2.11	4.7	4.05	0.38	0.85	0.45	1.59	0.82	3
12	47.7	1.12	5	4.29	0.84	-1.68	-0.24	-0.34	-0.35	10
13	31.5	1.32	4.5	4.19	-2.26	-1.16	0.91	0.46	-0.51	14
14	48.7	2.56	4.96	4.19	1.03	2.00	-0.15	0.46	0.84	2
15	46.7	1.62	4.78	4.22	0.65	-0.40	0.27	0.22	0.18	6
16	43.7	1.87	4.85	4.1	0.08	0.24	0.11	1.19	0.40	4
17	44.8	1.34	4.85	4.12	0.29	-1.11	0.11	1.03	0.08	8
18	43.3	1.8	4.9	4.2						
19	5.2	0.4	0.4	0.1						

Figure 5. Formula to calculate *z*-scores, in which the squad’s average test score (cell A18) is subtracted from the athlete’s test score (cell A2), then this value is divided by the squad’s standard deviation (cell A19). So this formula can then be dragged down and across to compute *z*-scores for all athletes across all tests, the row number for the mean and standard deviation must be fixed using the “\$”. Of note, the *z*-score can also be computed by using the “STANDARDIZE” formula in Excel.

RANK										
	A	B	C	D	E	F	G	H	I	J
1	Best_CMJ	Best_RSI	Best_Agility	Best_30m	Z_CMJ	Z_RSI	Z_Agility	z_30m	TSA	Rank
2	47.7	1.6	5	4.5	0.84	-0.45	-0.24	-2.04	-0.47	13
3	36	1.63	4.9	4.46	-1.40	-0.37	-0.01	-1.71	-0.87	16
4	42.8	1.72	6.4	4.19	-0.10	-0.14	-3.45	0.46	-0.81	15
5	51.2	2.5	4.4	4.34	1.51	1.85	1.14	-0.75	0.94	1
6	37	2.02	4.6	4.25	-1.20	0.62	0.68	-0.02	0.02	9
7	45.1	1.81	4.8	4.16	0.34	0.09	0.22	0.71	0.34	5
8	39.6	1.59	4.9	4.28	-0.71	-0.48	-0.01	-0.26	-0.36	11
9	44.9	1.94	4.9	4.25	0.31	0.42	-0.01	-0.02	0.17	7
10	40.1	1.67	4.8	4.37	-0.61	-0.27	0.22	-0.99	-0.41	12
11	45.3	2.11	4.7	4.05	0.38	0.85	0.45	1.59	0.82	3
12	47.7	1.12	5	4.29	0.84	-1.68	-0.24	-0.34	-0.35	10
13	31.5	1.32	4.5	4.19	-2.26	-1.16	0.91	0.46	-0.51	14
14	48.7	2.56	4.96	4.19	1.03	2.00	-0.15	0.46	0.84	2
15	46.7	1.62	4.78	4.22	0.65	-0.40	0.27	0.22	0.18	6
16	43.7	1.87	4.85	4.1	0.08	0.24	0.11	1.19	0.40	4
17	44.8	1.34	4.85	4.12	0.29	-1.11	0.11	1.03	0.08	8
18	43.3	1.8	4.9	4.2						
19	5.2	0.4	0.4	0.1						

Figure 6. For purposes of drawing graphs and to ensure scores above the line are seen as strengths, and those below the line are seen as weaknesses (and “windows of opportunity”), multiple speed based tests by -1

RANK										
	A	B	C	D	E	F	G	H	I	J
1	Best_CMJ	Best_RSI	Best_Agility	Best_30m	Z_CMJ	Z_RSI	z_Agility	z_30m	TSA	Rank
2	47.7	1.6	5	4.5	0.84	-0.45	-0.24	-2.04	-0.47	13
3	36	1.63	4.9	4.46	-1.40	-0.37	-0.01	-1.71	-0.87	16
4	42.8	1.72	6.4	4.19	-0.10	-0.14	-3.45	0.46	-0.81	15
5	51.2	2.5	4.4	4.34	1.51	1.85	1.14	-0.75	0.94	1
6	37	2.02	4.6	4.25	-1.20	0.62	0.68	-0.02	0.02	9
7	45.1	1.81	4.8	4.16	0.34	0.09	0.22	0.71	0.34	5
8	39.6	1.59	4.9	4.28	-0.71	-0.48	-0.01	-0.26	-0.36	11
9	44.9	1.94	4.9	4.25	0.31	0.42	-0.01	-0.02	0.17	7
10	40.1	1.67	4.8	4.37	-0.61	-0.27	0.22	-0.99	-0.41	12
11	45.3	2.11	4.7	4.05	0.38	0.85	0.45	1.59	0.82	3
12	47.7	1.12	5	4.29	0.84	-1.68	-0.24	-0.34	-0.35	10
13	31.5	1.32	4.5	4.19	-2.26	-1.16	0.91	0.46	-0.51	14
14	48.7	2.56	4.96	4.19	1.03	2.00	-0.15	0.46	0.84	2
15	46.7	1.62	4.78	4.22	0.65	-0.40	0.27	0.22	0.18	6
16	43.7	1.87	4.85	4.1	0.08	0.24	0.11	1.19	0.40	4
17	44.8	1.34	4.85	4.12	0.29	-1.11	0.11	1.03	0.08	8
18	43.3	1.8	4.9	4.2						
19	5.2	0.4	0.4	0.1						

Figure 7. The Total Score of Athleticism (TSA) is calculated by averaging all z-scores

RANK										
	A	B	C	D	E	F	G	H	I	J
1	Best_CMJ	Best_RSI	Best_Agility	Best_30m	Z_CMJ	Z_RSI	z_Agility	z_30m	TSA	Rank
2	47.7	1.6	5	4.5	0.84	-0.45	-0.24	-2.04	-0.47	13
3	36	1.63	4.9	4.46	-1.40	-0.37	-0.01	-1.71	-0.87	16
4	42.8	1.72	6.4	4.19	-0.10	-0.14	-3.45	0.46	-0.81	15
5	51.2	2.5	4.4	4.34	1.51	1.85	1.14	-0.75	0.94	1
6	37	2.02	4.6	4.25	-1.20	0.62	0.68	-0.02	0.02	9
7	45.1	1.81	4.8	4.16	0.34	0.09	0.22	0.71	0.34	5
8	39.6	1.59	4.9	4.28	-0.71	-0.48	-0.01	-0.26	-0.36	11
9	44.9	1.94	4.9	4.25	0.31	0.42	-0.01	-0.02	0.17	7
10	40.1	1.67	4.8	4.37	-0.61	-0.27	0.22	-0.99	-0.41	12
11	45.3	2.11	4.7	4.05	0.38	0.85	0.45	1.59	0.82	3
12	47.7	1.12	5	4.29	0.84	-1.68	-0.24	-0.34	-0.35	10
13	31.5	1.32	4.5	4.19	-2.26	-1.16	0.91	0.46	-0.51	14
14	48.7	2.56	4.96	4.19	1.03	2.00	-0.15	0.46	0.84	2
15	46.7	1.62	4.78	4.22	0.65	-0.40	0.27	0.22	0.18	6
16	43.7	1.87	4.85	4.1	0.08	0.24	0.11	1.19	0.40	4
17	44.8	1.34	4.85	4.12	0.29	-1.11	0.11	1.03	0.08	8
18	43.3	1.8	4.9	4.2						
19	5.2	0.4	0.4	0.1						

Figure 8. To ease interpretation for coaches and athletes, the TSA and each test’s z-score for that matter, can then be ranked and a “traffic light” system can be used to highlight how each athlete’s fitness compares to their team mates.

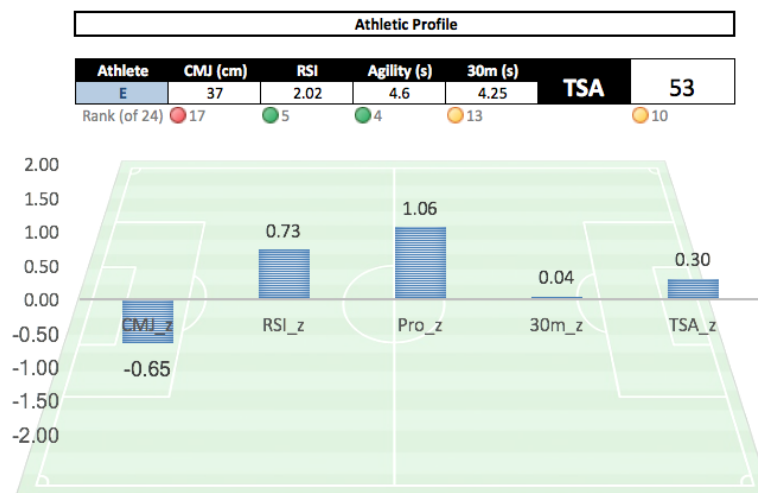


Figure 9. An example of how z-score data can be presented to coaches and athletes using the TSA, rankings, traffic light system, and a histogram (and using the “VLOOKUP” function). The actual TSA score in this example is 0.30, as noted on the graph. However, just above in the boxes, it is reported as 53. This is because the z-score derived TSA has been converted to represent a score between 0-100, which is more relatable for athletes and coaches. The conversion for this is described in the converting z-scores to *t*-scores section.

Converting z-scores to *t*-scores

There are actually two forms of *t*-scores, one used to transform *z*-scores in to more user-friendly numbers, which we will discuss now, and one used to standardize scores in small squads, which we will discuss in the following section. So, some coaches and athletes may not like the format of a *z*-score, that is a small number that can be positive or negative. In these instances, or just through general preference, *z*-scores can be converted to *t*-scores using the following formula: $t = (z * 10) + 50$ (see Figure 10). In this format, 50 represents the mean value (as oppose to 0 in *z*-scores), with 10 used to represent an interval equivalent to 1 SD (O'Donoghue, 2012). Therefore, a score of 60 represents a score that is 1 SD above the mean, and 70 two SD above the mean. Conversely, a score of 40 represents a score that is 1 SD below the mean and 30 two SD below the mean. We should also point out that raw scores can be directly converted to *t*-scores using the following formula: $t = 50 + 10 (\text{athlete score} - \text{team mean}) / \text{team SD}$ (see Figure 11). Because *t*-scores produce a number that is more conventionally appreciated by athletes, that is, it provides a scores between 0-100 rather than -5 to 5 (as per *z*-scores), the final overall TSA score is presented in this way as illustrated in Figure 9. Anecdotally however, it may still be better to illustrate any data contained in

graphs via z -scores, as these more readily illustrate better and worse than average (and by what magnitude) via bars being above or below the y -axis.

fx = (F2*10)+50

F	G	H	I	J	L	M	N	O	P
z CMJ	z RSI	z Agilit	z 30m	TSA (z)	t CMJ	t RSI	t Agility	t-30m	TSA (t)
0.84	-0.45	-0.24	-2.04	-0.47	= (F2*10)+50	45	48	30	45
-1.40	-0.37	-0.01	-1.71	-0.87	36	46	50	33	41
-0.10	-0.14	-3.45	0.46	-0.81	49	49	16	55	42
1.51	1.85	1.14	-0.75	0.94	65	68	61	43	59
-1.20	0.62	0.68	-0.02	0.02	38	56	57	50	50
0.34	0.09	0.22	0.71	0.34	53	51	52	57	53
-0.71	-0.48	-0.01	-0.26	-0.36	43	45	50	47	46
0.31	0.42	-0.01	-0.02	0.17	53	54	50	50	52
-0.61	-0.27	0.22	-0.99	-0.41	44	47	52	40	46
0.38	0.85	0.45	1.59	0.82	54	59	55	66	58
0.84	-1.68	-0.24	-0.34	-0.35	58	33	48	47	46
-2.26	-1.16	0.91	0.46	-0.51	27	38	59	55	45
1.03	2.00	-0.15	0.46	0.84	60	70	49	55	58
0.65	-0.40	0.27	0.22	0.18	56	46	53	52	52
0.08	0.24	0.11	1.19	0.40	51	52	51	62	54
0.29	-1.11	0.11	1.03	0.08	53	39	51	60	51

Figure 10. Converting z -scores to t -scores using the formula $t = (z * 10) + 50$

fx = 50+10*(B2-B\$18)/B\$19

B	C	D	E	Q	R	S	T	U
Best CMJ	Best RSI	Best Agilit	Best 30m	t CMJ	t RSI	t Agility	t-30m	TSA (t)
47.7	1.6	5	4.5	B\$18/B\$19	45	48	30	45
36	1.63	4.9	4.46	36	46	50	33	41
42.8	1.72	6.4	4.19	49	49	16	55	42
51.2	2.5	4.4	4.34	65	68	61	43	59
37	2.02	4.6	4.25	38	56	57	50	50
45.1	1.81	4.8	4.16	53	51	52	57	53
39.6	1.59	4.9	4.28	43	45	50	47	46
44.9	1.94	4.9	4.25	53	54	50	50	52
40.1	1.67	4.8	4.37	44	47	52	40	46
45.3	2.11	4.7	4.05	54	59	55	66	58
47.7	1.12	5	4.29	58	33	48	47	46
31.5	1.32	4.5	4.19	27	38	59	55	45
48.7	2.56	4.96	4.19	60	70	49	55	58
46.7	1.62	4.78	4.22	56	46	53	52	52
43.7	1.87	4.85	4.1	51	52	51	62	54
44.8	1.34	4.85	4.12	53	39	51	60	51
43.3	1.8	4.9	4.2					
5.2	0.4	0.4	0.1					

Figure 11. Converting raw scores to t -scores using the formula $t = 50 + 10 (\text{athlete score} - \text{team mean}) / \text{team SD}$

Fitness testing for small squads

The use of z -scores normally requires achieving one of two conditions. Firstly, normally distributed data (as illustrated in figure 2), which given the central limit theorem, is achieved with a sample size of > 30 (Field, 2018). Secondly, it requires us to know the population SD (σ), which in reality, is rarely known. Therefore, when testing players from a squad of < 30 , the data is likely to follow a t -distribution, which is essentially shorter and fatter than the normal distribution associated with z -scores (Field, 2018). In these instances, where the shape of the curve is dependent on sample size, reference tables must be used to interpret the magnitude of difference for the assessed value relative to the mean; that is as oppose to z -scores where a value of 1 always infers a 34% difference relative to the mean (see Figure 2). Therefore, if we were to use z -

fx =PERCENTRANK(AZ\$2:AZ\$25,AZ3)

AY	AZ	BA	BB
t_30m	TSA_t	Rank	Percentrank
-6.11	-2.21	19	PERCENTRA
1.99	-3.12	20	17%
-2.51	4.96	2	96%
0.19	1.45	10	61%
2.88	2.19	7	74%
1.69	-0.36	13	48%
-0.71	-0.43	14	43%
0.19	1.57	8	70%
-3.41	-0.52	15	39%
6.18	4.17	4	87%
-1.01	-0.88	17	30%
1.99	-0.60	16	35%
1.99	4.91	3	91%
1.09	1.51	9	65%
4.68	2.46	6	78%
5.58	3.88	5	83%
4.08	0.99	11	57%
8.88	8.94	1	100%
-4.61	-4.64	22	9%
-12.70	-8.49	24	0%
-4.61	-6.19	23	4%
4.38	0.17	12	52%
-2.81	-3.83	21	13%

Figure 13. Using the PERCENTRANK formula in excel to convert *t*-score based TSA scores in to percentages, whereby 50% represents the mean.

In closing, a player profile produced using *t*-scores is presented in Figure 14; this is the same player used above in Figure 9, allowing you to note the subtle difference between the two methods of analysis. Incidentally, the rank you get from *t*-score analysis is generally identical to the rank you get from a *z*-score analysis; it is just unfortunate that *t*-scores (unlike *z*-scores) are affected by sample size and thus require reference tables to determine relative difference from the mean.

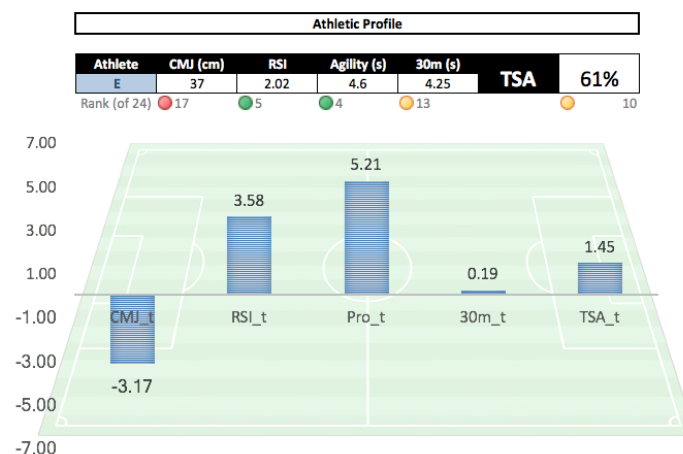


Figure 9. An example of how *t*-score data can be presented to coaches and athletes using the TSA, rankings, traffic light system, and a histogram (and using the “VLOOKUP” function). The actual TSA score in this example is 1.45, as noted on the graph. However, just above in the boxes, it is reported as 61%. This is because the *t*-score derived TSA has been converted to represent a

percentage score between 0-100, which is more relatable for athletes and coaches. The conversion for this is achieved via the “PERCENTRANK” function in excel.

Conclusion

Oftentimes, the coaching staff that make up the multidisciplinary team of a sports club or governing body require a single, holistic, indication of an athlete’s athleticism. Currently there is no consensus on how this is best achieved and thus the TSA may provide one such strategy. The validity of the TSA score is largely determined by the relevance of the fitness tests used, so coaches must be able to rationalize their choices based on the information derived from a comprehensive needs analysis of the sport including positional demands.

Finally, data visualization is an important consideration to maximize the effectiveness of this approach. The figure schematic used is such that it is relatively simple to interpret for both coaches and athletes. Histograms may provide a logical and easy way to understand the data, as scores above the line mean an athlete is better than average, while below the line suggests they are worse, the height of the bar determines by how much. This information can then be used to identify areas to be targeted when the next training program is individualized for each athlete. Of course, it would be remiss of us to not point out that standardized scores essentially rank athletes within the tested population, thus half the athletes will always be below average. Some consideration should therefore be given to whether this highlights windows of opportunity in these athletes, or is a natural byproduct of exceptional fitness within the tested squad. If it were the latter, then other areas should be targeted, with this a natural consequence of analysis via standardized scores. For interested readers, a step-by-step guide for the calculation of z -scores and the TSA, along with how to graph results (as histogram or radar plot) is available elsewhere (Turner, 2017).

References

1. Bunn, J., Ryan, G., Button, G., & Zhang, S. (2017). Evaluation of strength and conditioning measures with game success in Division I collegiate volleyball: A retrospective study. *Journal of strength and conditioning research*.
2. Field, A. (2018). *Discovering statistics using IBM SPSS statistics*. London: Sage.

3. Jones, B., Till, K., Manley, A., & McGuigan, M. (2017). A Multidisciplinary Approach to the Profiling and Interpretation of Fitness Testing Data: A Case Study Example. *Journal of Australian Strength and Conditioning Research*, 25(1), 31-36.
4. Long, G., Walker, J., Herron, R., Bishop, S., Katica, C., & Ryan, G. (2014). Predicting caliber of performance and on field contribution of NAIA division football players. *International Journal of Exercise Science: Conference Proceedings*, 8, p. 68.
5. O'Donoghue, P. (2012). *Statistics for sport and exercise studies: An introduction*. Oxon: Routledge.
6. Salkind, N. (2011). *Statistics for people who hate statistics*. London: Sage.
7. Till, K., Jones, B., Cobley, S., Morley, D., O'Hara, J., Chapman, C., & Beggs, C. (2016). Identifying talent in youth sport: a novel methodology using higher-dimensional analysis. *PLoS One*, 11(5), e0155047.
8. Till, K., Scantlebury, S., & Jones, B. (2017). Anthropometric and physical qualities of elite male youth rugby league players. *Sports Medicine*, 47(11), 2171-2186.
9. Turner, A. (2014). Total Score of Athleticism: a strategy for assessing an athlete's athleticism. *Profesional Strength and Conditioning*, 33, 13-17.
10. Turner, A. (2017, June 17). *Z-scores and the TSA*. Retrieved from Youtube: <https://www.youtube.com/watch?v=6l5VdBlo96Y>
11. Wing, C., Turner, A., & Bishop, C. (2018). The Importance of Strength and Power on Key Performance Indicators in Elite Youth Soccer. *Journal of strength and conditioning research*.